

Statistical Modeling of Combat Mortality Events by Using Subject Matter Expert Opinions and Operation Iraqi Freedom Empirical Results from the Navy–Marine Corps Combat Trauma Registry

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Abstract

In 12 Navy–Marine Corps medical logistics studies and analyses conducted by the Naval Health Research Center (NHRC) and Teledyne Brown Engineering (TBE) over the past 5 years, estimates of battlefield mortality have been a major metric of interest to medical planners. An ongoing concern is how mortality is related to delays in treatment for medical logistics reasons. In this paper, we describe how NHRC and TBE have been developing a statistically based model for mortality since 2003, first starting with panel results from a group of military medical doctors and continuing here with an analysis of empirical injury data from Operation Iraqi Freedom (OIF). The panel results and statistical analysis of life-threatening injury data in OIF from early 2004 to mid-2006 indicate that the Weibull distribution describes the timing of high risk of mortality events in a reasonable manner within surgical medical treatment facilities. The quest for a best-fitting probability distribution with parameters dependent on the casualty flow chain of treatment and evacuation in the theater is ongoing. In reality, combining analytical and subject matter expert (SME) results to model mortality is necessary given the breadth of theater medical delivery systems and general paucity of adequate empirical data in many of the segments of patient flow.

Keywords

combat mortality, Navy–Marine Corps Combat Trauma Registry, statistical modeling, Weibull probability distribution

1. Introduction

The Naval Health Research Center's (NHRC) Tactical Medical Logistics (TML+) planning tool aids the medical planner by simulating, in a systems sense, a broad range of stochastic events associated with a battlefield casualty's disposition from the point-of-injury (POI) to definitive care (<http://www.tmlsim.com>). As designed and developed during FY01 to FY07, TML+ is a software program for medical planners that estimates medical resource requirements using data from the Estimating Supplies Program (ESP).¹ It permits a broad range of operational risk assessments, medical systems analysis, and operations research studies to be conducted for a variety of scenarios. The tool assumes a systems view of the tactical Medical Treatment Facility (MTF) network within the theater, where the MTFs are integrated with transportation assets and compete for medical/logistics resources (staff, equipment, consumables, transporters) as casualties flow through the system. Other recent modeling

and simulation (M&S) work of a similar combat medical logistics systems nature is described by von Tersch et al.²

The TML+ output metric that has been of paramount interest in 12 theater medical planning studies over the past 5 years is the died-of-wounds (DOW) due to a delay in treatment mortality estimate.³ Typical questions of interest have included the following:

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1. How many lives can be saved if a forward surgery system is present near the combat area?
2. What is the best way to integrate, in time and space, transportation and MTF assets to reduce casualty losses in a deployed network of care?
3. How do spikes in casualty occurrences impact operating room throughput and mortality for various staff and equipment configurations?

The primary objective of this research report is to document NHRC's ongoing effort to develop a statistically based model for TML+ and other medical systems analysis models that projects the effects of treatment delays and the extent of resuscitation available (surgical-level resuscitation versus non-surgical-level resuscitation) on battlefield mortality. This empirically based capability, perhaps merged with available subject matter expert (SME) results, would allow medical planners to more confidently estimate the mortality risk associated with candidate operational courses of action (COAs) for either deliberate planning in the future or for crisis action planning for real-time deployments.

2. Background

For use in NHRC's TML+ discrete event simulation, it is assumed that a seriously wounded casualty's time to death is a random variable that has a probability density function (pdf) with parameters dependent on the casualty's injury extent, current MTF capability, and past treatment history/timing. In the model, simulated draws are made from the pdf throughout a scenario to interject mortality events. The Weibull pdf, to be described later, is currently used in TML+ based on an analysis of expert opinion data obtained from a panel of nine military medical doctors convened at NHRC in November 2003.⁴⁻⁷ The work by von Tersch et al.² describes a mortality model that is graphical in nature, and, indeed, is similar to a subjective algorithm used in TML+ in an earlier version in the 2000 timeframe.⁸ As empirical injury records are now available for Operation Iraqi Freedom (OIF) combat, as will be introduced in the next section, we seek a more objective data-driven stochastic model for use in TML+ and one perhaps of interest to other medical M&S efforts.

For the modeling approach used in TML+, an obvious research goal is to confirm/update the expert panel results with a statistical analysis of empirical mortality results. A prerequisite of this analysis is a large number of recorded life-threatening (LT) incidents from an operational scenario with sufficient timing information on treatment entry and disposition. Real-world casualty resuscitative data from the Navy-Marine Corps Combat Trauma Registry Expeditionary Medical Encounter Databases (NMC CTR EMED) on OIF injuries are used to examine the efficacy of confirming and/or supplementing the panel results with a time-based

mortality analysis.⁹ The analysis file available covers the period from early 2004 to mid-2006 and contains 1079 injury records deemed to be of a LT nature.¹⁰ While certain results applicable to TML+ were obtained and will be illustrated, several inherent limitations in the NMC CTR data structure preclude a full investigation of battlefield mortality as a function of detailed casualty flow paths and delays in treatment as assumed in TML+.¹¹ These limitations will be addressed as topics for future research.

This paper is organized as follows: a brief description of the SME panel results is given in Section 3; statistical analysis results of NMC CTR OIF mortality events using techniques from the biostatistics and applied life data analysis literature for certain resuscitative capable MTFs are given in Section 4; a graphical comparison with SME panel results is given in Section 5; and, finally, suggested future activities to extend this research to more completely model mortality in terms of treatment delays and additional casualty flow variations are discussed in Section 6.

3. Initial Modeling Results Inferred from Subject Matter Expert Opinions

Figure 1 shows subjective observations and estimated results from a 2003 medical doctor SME panel^{5,7} for a patient with a high risk of mortality injury. In the figure, the casualty is presumed to receive a series of medical interventions for a LT injury:

1. by self or a buddy at the point of injury (labeled 'no treatment');
2. by a field-level corpsman (first responder) after a 10-minute delay;
3. by the Battalion Aid Station (BAS) MTF after a 30-minute delay; and, finally,
4. by a Shock Trauma Platoon (STP)/Forward Resuscitative Surgical System (FRSS) MTF after 30 minutes of delay.

The results illustrate how medical treatment improves survival as the casualty moves through the MTF system. Curves of this nature are used in TML+ to simulate a time of death as a seriously wounded patient flows through the battlefield medical chain of treatment and evacuation.¹² The estimated results in the figure presume a Weibull pdf, where the parameters are estimated by the ad hoc analytical method of matching a few percentile points (Elandt-Johnson and Johnson,¹³ p. 182). The more standard analytical method of maximum likelihood, including all of the observations, will be used for the empirical results to be described later.

By convention, we define LT injuries as those where a casualty is expected to die within the first hour after injury (the 'golden hour') if no treatment beyond first-aid is received by either the individual casualty or from a 'buddy'.

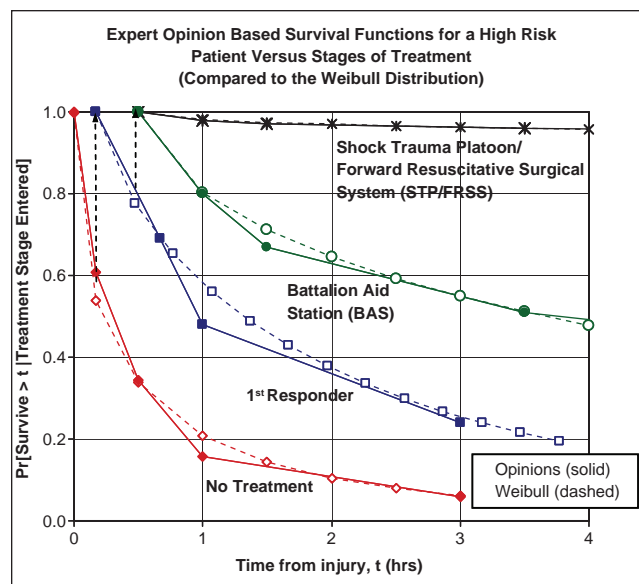


Figure 1. Expert panel survivability opinions and initial Weibull fit for a seriously injured patient

In TML+, LT injuries are identified through patient conditions (PCs) that are designated as having either a high, medium, or low risk of mortality within the first hour after wounding, where the probability of dying is greater than 2/3, between 1/3 and 2/3, or less than 1/3, respectively.^{5,14}

The panel was conducted in a Delphi-similar manner, where a presumed number of battlefield casualties with various PCs developed by the Defense Medical Standardization Board and used in NHRC's M&S efforts were assumed to be initially injured.¹⁵ For each PC and treatment assumption, the panel was asked to estimate the fraction of casualties that would be expected to survive after specified time epochs, such as 10 minutes, 30 minutes, 1 hour, 3 hours, etc., in the various interventions or MTFs. An average value of their opinions and the Weibull estimates are shown in Figure 1. The rather impressive matching of these expert, yet qualitative, opinion results with the Weibull distribution is encouraging for the pursuit of a stochastic representation and was judged adequate for an initial implementation in TML+. Similar curves for medium and low risks of mortality were obtained.

4. Statistical Analysis Results from Navy-Marine Corps Combat Trauma Registry Data

The NMC CTR is a data warehouse composed of data sets describing events that occur to individual casualties, from the POI through the medical chain of evacuation and on to long-term rehabilitative outcomes.⁹ The CTR can assist medical planners, systems analysts, and logisticians in planning

for the random occurrence of injury types in treatment and evacuation scenarios of interest. These data sets provide the empirical means to confirm or augment medical logistics modeling assumptions to better quantify the optimal mix of health-care facilities and providers, medical equipment and supplies, and transportation assets affecting battlefield medical delivery. In this section, we explore the utility of using NMC CTR records in a statistical analysis to provide a probability distribution for the simulated timing of deaths within a MTF, a distribution perhaps dependent on prior treatment paths as currently modeled in TML+.

Table 1 shows a screen shot of a very small subset of the CTR data file. The timing of injury events and MTF entry/exits along with the disposition data is of primary interest in the file but is suppressed in the table to avoid privacy issues. The Injury Severity Score (ISS)¹⁶ is one of the many elements in this file for an individual injury and is the basis for LT records we will analyze.

4.1 Using the ISS as a Metric for the Risk of Mortality

In using the ISS, it is assumed that values less than 9 correspond to injuries that are not life-threatening and values of 9 or larger correspond to life-threatening injuries. Furthermore, life-threatening values between 9 and 14 correspond to a low risk of mortality, values between 15 and 24 correspond to a medium risk, and values of 25 and above correspond to a high risk. The OIF data file with ISS values greater than or equal to 9 was slightly over 1000 records. Of these, about 80% corresponded to patient records at MTF level IIa (surgical) facilities. The approximately 20% of records remaining were from several MTFs (BAS and STP), none of which taken separately represented a large enough sample judged to be adequate for a statistical analysis.

Too few surgical facility arrivals had detailed information on time of wounding or any record of prior treatment to permit a reasonable statistical analysis of the mortality effects due to specific paths or delays in arrival (original goals). However, the patients with complete timing information on arrivals and departures did allow an investigation of the nature of the random variable for the time to death in a surgical facility. The effects of delays in treatment and the effects within a MTF are both important in modeling casualty mortality in a simulation tool. It is expected that additional records to allow an empirical study of the treatment delay effects will be available in the future.

For the subset of high-risk patients with sufficient timing information on arrivals and departures, some 160 records with ISS values ≥ 25 were available across all surgical facilities. Of these, 26 (17.1%) were labeled DOWs for a surgical facility disposition, and the remaining 134 were labeled as evacuations to the next higher MTF. Corresponding groups of medium- and low-risk patients contained less than

Table 1. A desensitized portion of the combat trauma registry (CTR)

Case ID	Medical Treatment Facility ID	Arrival Method	Injury severity Score	Triage Category	Injury Category	Subjective Assessment (SOAP) notes	Objective Plan	Disposition	Evac Priority	Many more data entries →
1111	Battalion Aid Station 2/6	Non-Medical Ground	34	Immediate	Blunt	Patient brought to Fox Co Firm Base after IED exploded 4-6 feet from him. Marines on scene state he was thrown 10-15 feet from force of blast. ...		Surgical Company Charlie	Urgent	
1112	Shock Trauma Platoon / Forward Resuscitative Surgical System 2	Casualty Evacuation (CASEVAC) system	57	Immediate	Amputation	Probable RPG round through abdomen, chest and arm. Initially treated at BAS with valve dressing over chest ...		Died-of-Wounds (DOW)		
1113	Shock Trauma Platoon / Forward Resuscitative Surgical System 7	Medical Air	13	Immediate	Penetrating	20 y/o ad USMC, IED rear passenger HMWVV. C/O B/L leg pain, no LOC, ...		Evacuated	Urgent	
1114	Battalion Aid Station 2/6	Casualty Evacuation (CASEVAC) system	9	Immediate	Perforating	Patient suffered GSW to ... aspect of neck. Wound approx 5cm just inferior to mandibular angle, ...		Evacuated	Priority	
1115	Surgical Company Charlie	Casualty Evacuation (CASEVAC) system	26	Immediate	Hemothorax	18 y/o Marine - driver of High-backed Humvee struck by blast of IED. Occurred 30min prior to arrival. Per Corpsman ...		Died-of-Wounds (DOW)		

40 cases and were judged too small for consideration. The next section presents a statistical analysis of these 160 data results.

4.2 Statistical Results for the ISS-derived Surgical Facility High-Risk Records

If we can reasonably demonstrate the characteristics of mortality within a MTF to include the shape of a distribution via a pdf, we can simulate a discrete event in TML+ to represent DOW timing. Candidates often used in mortality studies include the exponential, gamma, lognormal, Gompertz, and Weibull distributions.¹³ As the 2003 MD SME panel results suggested the Weibull distribution, it is our first choice here. If the Weibull's fit to the data is deemed unsatisfactory, other models will be examined. The life insurance industry typically uses actuarial tables to determine expected lifetimes underlying policy premiums and do not often depend on simulated individual death

times as required in a medical logistics systems analysis tool such as TML+.¹³ Hardware reliability and biomedical sciences applications typically use distributions from the set described above.^{13,17,18}

Figure 2 shows a time-ordered plot of the total DOWs and evacuations for the $ISS \geq 25$ set. It also shows the number of surgical patients remaining at risk versus time, computed by subtracting the total number of DOWs and evacuations from the entry number (160). These are called progressively censored samples in the literature of biomedical sciences and life data analysis as patients enter and leave at differing times, and deaths are intermixed with withdrawals where the patient is alive.^{13,17,18}

Throughout, the random life time T is assumed to have a pdf $f(t)$ and a probability of surviving past time t given by the survival function $S(t) = \Pr[T \geq t]$. To correspond to the MD SME panel observations, we examine here the usefulness of the Weibull distribution in describing mortality in the CTR data set available. The density function with

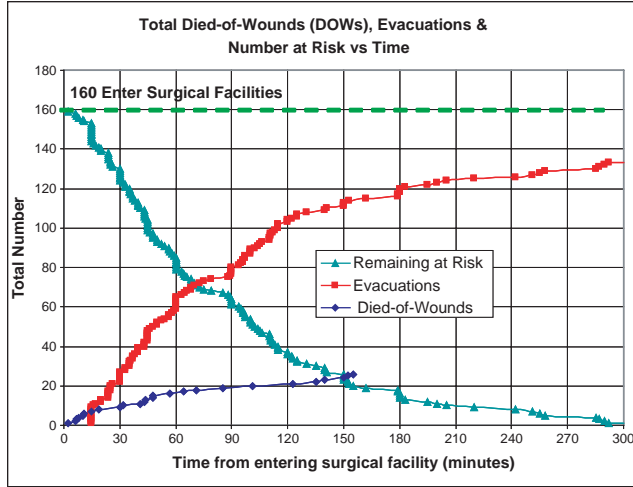


Figure 2. Time histories for total died-of-wounds, evacuations, and patients at risk ($n = 160$, surgical facility case)

parameters $\{a, b\}$ and corresponding survival function for the Weibull are¹⁸

$$f(t; a, b) = \frac{b}{a} \left(\frac{t}{a} \right)^{b-1} e^{-\left(\frac{t}{a} \right)^b}, \quad a > 0, b > 0, t > 0 \quad (1)$$

and

$$S(t) = e^{-\left(\frac{t}{a} \right)^b}. \quad (2)$$

The hazard function, $h(t)$, and cumulative hazard function, $H(t)$, are also used in the following. Their equations are

$$h(t) = \frac{f(t)}{S(t)} = \frac{b}{a} \left(\frac{t}{a} \right)^{b-1} \quad (3)$$

and

$$H(t) = \left(\frac{t}{a} \right)^b \quad (4)$$

where $h(s)$ is integrated from $s = 0$ to t . The exponential pdf is a special case of the Weibull pdf, where the shape parameter b is 1.0; its hazard rate is constant. The parameter a is called the scale parameter.

The survival function, $S(t)$, and hazard function, $h(t)$, each giving a different view or interpretation of the mortality process, will be estimated from data plots and analytical means in the next section. (Basically, the lengths of life times via the survival function and the rate at which deaths occur [given by the hazard function] are different views of the same process.)

It is assumed that the patients entering the surgical MTFs are a random sample from the OIF severely injured population, and the injuries incurred are a random sample of the battlefield wounds likely from OIF theater operations. It is further assumed that the majority of patients arrive at the

surgical MTFs directly from first responder treatment after a nominal delay. Our basic approach will be to characterize the pdf of T by exploiting various features of the Weibull distribution.

4.3 Weibull Parameters via Graphical and Maximum Likelihood Methods of Estimation

A caveat first: the data presented here are said to be right censored in that the dependent variable, death time, for the patients who were evacuated is known to be greater than the time of withdrawal, but the true value is unknown. These are often called incomplete samples. It is assumed that if these patients had remained in a surgical facility, their subsequent death times would be from the same probability distribution as that observed for the DOWs, i.e. we assume that the censoring process is non-informative of future survivability. This is a common assumption in the literature for graphical and analytical techniques applied to life data of this nature (Nelson,¹⁸ p. 315).

Probability theory provides essential tools for survival analyses of this type of clinical data, but possibilities of departures from theoretical models are so great and varied that considerable detail is typically required for fitting distributions to observations—it is for these reasons that graphical methods are considered of first importance to compliment analytical methods such as maximum likelihood (Elandt-Johnson and Johnson,¹³ p.7). Nelson¹⁸ further comments that each method provides information not provided by the other, e.g., a plot helps to assess the validity of the assumed distribution and of the data, while analytical methods provide confidence limits and objective estimates. This is the approach that we follow.

Various non-parametric techniques exist to estimate the empirical survival function $S(t)$. One of the oldest is a so-called actuarial method dating back some 200 years that was developed and used to construct human life tables with grouped data by insurance companies for risk analysis. A more modern technique uses individual ordered observations in continuous time. Each technique seeks to estimate the probability of survival past some point in time. Estimates of the hazard function and the standard error of $S(t)$ are usually provided for each technique. Example results of these methods were provided in various NHRC/TBE technical interchange meetings.¹⁹ The so-called method of Kaplan–Meier in continuous time will be used here for a non-parametric estimate of $S(t)$ and related functions.^{17,18} The analytical method of maximum likelihood, assuming a Weibull distribution of life times, will also be used to estimate the parameters of $S(t)$.

Referring again to Figure 2, the basic idea presented by Kaplan and Meier is to order the intermixed death and evacuation times and compute the survival function after each

Table 2. Example data showing the Kaplan–Meier estimates of the survival function, $S(t)$, for the first 20 minutes after surgical facility entry

Event Time t , min	Event	0-censor 1-complete	Nbr Remain at t , r_i	Kaplan–Meier Est of $S(t)$
2	DOW	1	160	0.994
6	DOW	1	159	0.988
7	DOW	1	158	0.981
8	DOW	1	157	0.975
10	DOW	1	156	0.969
11	DOW	1	155	0.963
15	DOW	1	154	0.956
15	Evac	0	153	0.956
15	Evac	0	152	0.956
15	Evac	0	151	0.956
15	Evac	0	150	0.956
15	Evac	0	149	0.956
15	Evac	0	148	0.956
15	Evac	0	147	0.956
15	Evac	0	146	0.956
15	Evac	0	145	0.956
16	Evac	0	144	0.956
17	Evac	0	143	0.956
19	DOW	1	142	0.950
20	Evac	0	141	0.950
...				

death using the recursive formula given below. Specifically, the Kaplan–Meier estimate of S_i after each death event at time t_i is

$$S_i = (r_i - 1)/r_i * S_{i-1}, S_0 = 1 \quad (5)$$

where r_i is the reverse rank of the i th death. If there are assumed to be n event times in the sample, they are ordered from smallest to largest and numbered backwards with reverse ranks. Table 2 illustrates the basic approach by showing the DOW and evacuation events for the initial 20 minutes within surgical MTFs, where evacuation times are labeled ‘0’ indicating censoring or incomplete data, and ‘1’ indicate death events, where the timing is known. Estimates of $S(t)$ are computed using Excel and shown in the table. Table 3 shows $S(t)$ results after each death event for the entire data set using the SYSTAT statistical software package.²⁰ It also shows various other mortality metrics indexed by the death times; the cumulative hazard function and Weibull entries will be discussed next.

The equation for the cumulative hazard function of the Weibull distribution in (4) can be transformed into

$$\log(t) = \frac{1}{b} \log H(t) + \log(a) \quad (6)$$

Table 3. SYSTAT computation for the Kaplan–Meier estimate of the survival function, $S(t)$, and other measures

Death Time t , min	Number At Risk	Number Dying	K-M Est of $S(t)$	Std Error of $S(t)$	Hazard Rate, $h(t)$	Cumulative Hazard, $H(t)$	Weibull Model Survival Prob (via MLE)
2	160	1	0.994	0.006	0.006	0.006	0.995
6	159	1	0.987	0.009	0.006	0.013	0.986
7	158	1	0.981	0.011	0.006	0.019	0.983
8	157	1	0.975	0.012	0.006	0.025	0.981
10	156	1	0.969	0.014	0.006	0.032	0.977
11	155	1	0.962	0.015	0.006	0.038	0.975
15	154	1	0.956	0.016	0.006	0.045	0.967
19	142	1	0.95	0.017	0.007	0.052	0.959
30	131	1	0.942	0.019	0.008	0.059	0.938
32	124	1	0.935	0.02	0.008	0.067	0.935
41	111	1	0.926	0.022	0.009	0.076	0.919
43	110	1	0.918	0.023	0.009	0.085	0.915
44	106	1	0.909	0.024	0.009	0.095	0.914
48	98	2	0.891	0.027	0.010	0.105	0.907
57	89	1	0.881	0.029	0.011	0.116	0.892
64	78	1	0.869	0.03	0.013	0.129	0.88
71	72	1	0.857	0.032	0.014	0.143	0.869
85	68	1	0.845	0.034	0.015	0.158	0.848
101	52	1	0.828	0.037	0.019	0.177	0.824
123	35	1	0.805	0.043	0.029	0.206	0.793
135	31	1	0.779	0.049	0.032	0.238	0.777
140	30	1	0.753	0.054	0.033	0.271	0.77
150	27	1	0.725	0.058	0.037	0.308	0.757
152	23	1	0.693	0.064	0.043	0.352	0.754
155	21	1	0.66	0.069	0.048	0.399	0.751

to give a linear relationship that can be exploited to estimate the parameters $\{a, b\}$ if the Weibull distribution applies to these data, i.e. if the log of time t versus the log of the cumulative hazard function plots as a straight line, then a simple graphical means results to visually gauge the viability of the Weibull distribution. Indeed, linear regression can be used to estimate the slope and intercept coefficients in Equation (6) via the technique of least-squares analysis to give quantitative estimates of the straight-line coefficients.²¹ Figure 3 shows the ordered pairs $(\log(H(t)), \log(t))$ computed from Table 3 entries and the fitted linear regression model. In the figure, $H(t)$ is estimated by summing the non-parametric estimates of the hazard rate, $h(t) = 1/k$, where k is the number remaining at risk at time t .

Obviously the Weibull distribution describes these surgical MTF data quite nicely, as indicated by the straight-line fit and near-perfect correlation value shown in the figure. Least-squares estimates can be transformed as indicated in Equation (6) to give the Weibull parameter estimates indicated. Next, we examine the maximum likelihood estimates (MLE) of $\{a, b\}$ via the techniques described by Nelson¹⁸ and compare the parametric model based on the Weibull distribution with the non-parametric Kaplan–Meier estimates given in Table 3. An approximate confidence interval will also be presented for the survival function. Before proceeding, we include a brief overview on the method of maximum likelihood.

The method of maximum likelihood seeks to determine the unknown parameters of a distribution to maximize the probability of obtaining the observed set of outcomes. A so-called likelihood function, which is the joint probability distribution of the known data and the unknown parameters, is formed and parameters are chosen to maximize this function. The approach thus provides estimators that agree most closely with the observed data. The likelihood function is typically complex, especially for applications with censored results, and statistical software is often required to perform the associated optimization: we used the SYSTAT package²⁰ to obtain the Weibull parameters in Equation (1) and the associated survival probability entries of Table 3.

Figure 4 shows the Kaplan–Meier non-parametric estimate of the survival function and also the estimate based on the parametric Weibull model (both from Table 3). Estimates of $\{a, b\}$ via the linear model transformation in Figure 3 agree quite well with the MLE values of Figure 4. Confidence intervals were not calculated for the parameters, but we suspect the interval for the shape parameter b would contain the value 1.0, indicating that the exponential special case of the Weibull would adequately describe these results. However, to be consistent with the smaller shape parameter values for MTFs prior to surgery as observed in the MD SME panel,^{5,7} we elect to standardize on the two-parameter version of the Weibull distribution until further results are available for analysis.

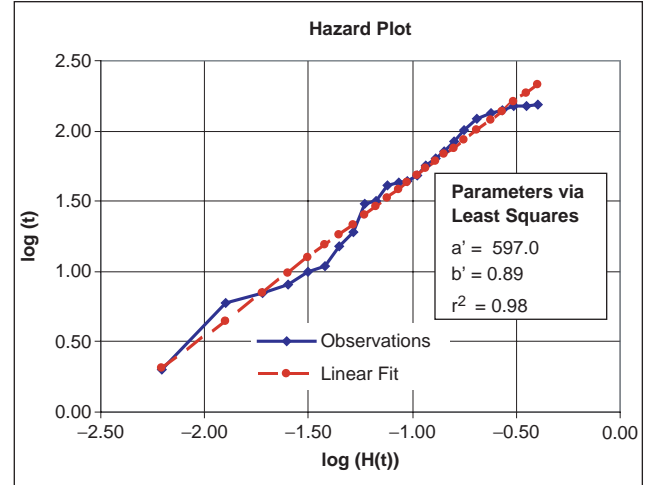


Figure 3. Log hazard plot and linear regression estimates of Weibull parameters $\{a, b\}$

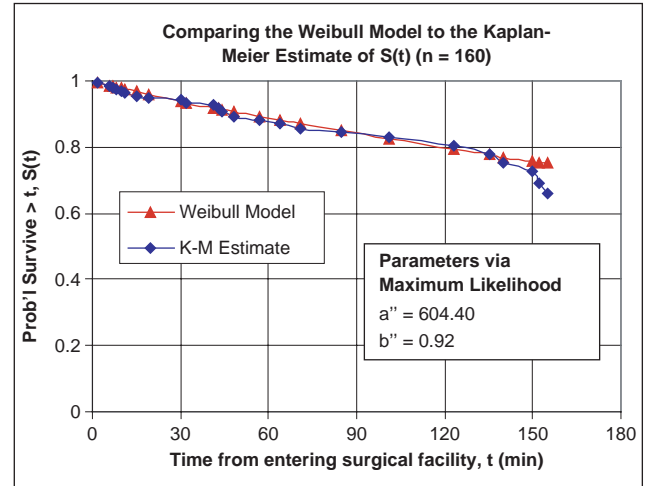


Figure 4. Non-parametric (Kaplan–Meier) and parametric (Weibull) estimates of the survival function, $S(t)$

Given the almost perfect straight-line fit of the Weibull hazard function to the empirical hazard function and the nice MLE agreement, both graphical and analytical methods suggest that the Weibull distribution is an adequate fit of mortality events in this case. For completeness, we did conduct a chi-squared goodness-of-fit test for a life table representation of the data on death times and numbers at risk in Table 3.²² A computed value of 3.63 was obtained, and when compared with the chi-squared tabular value of 5.99 with two degrees of freedom and an α of 0.05, a null hypothesis for the Weibull distribution to describe these data could not be rejected.

Figure 5 shows the approximate 95% confidence limits about the Weibull $S(t)$ estimate.¹⁸ For example, the probability of survival past 60 minutes is expected to lie between

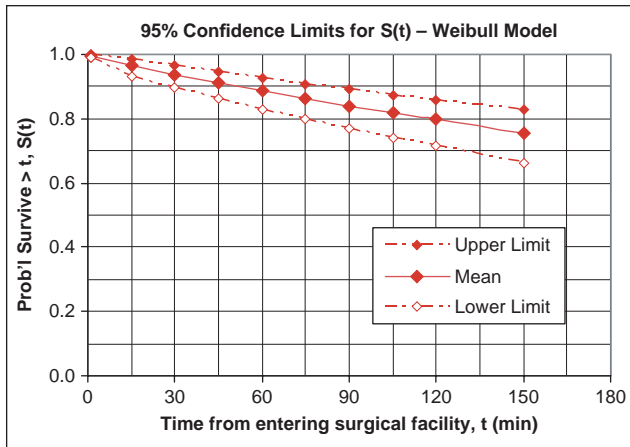


Figure 5. Approximate 95% confidence limits for estimation of the Weibull survival function, $S(t)$

approximately 0.83 and 0.92, where the mean estimate is about 0.88. In the next section, the fit of the Weibull distribution to the CTR data is graphically compared with the results from the MD SME panel.

5. Comparing the Combat Trauma Registry-based Modeling Estimates with the Expert Panel Results

We next superimpose curves from the MD SME panel on to the CTR-based confidence intervals in Figure 5. The two curves labeled ‘Panel- ...’ in Figure 6 come from the original data collection effort in 2003 for a high-risk PC and the casualty flow case ‘first responder to STP/FRSS’.⁵ These curves show how the panel expected delay times of 30 and 120 minutes from POI to surgical MTF entry to impact mortality after the casualty had started treatment there.

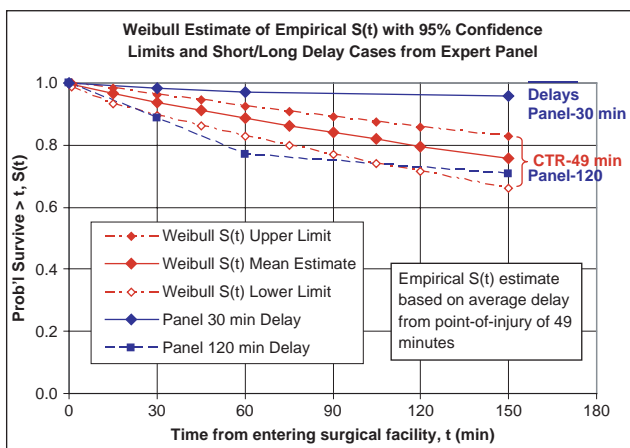


Figure 6. Weibull estimate of survival function, $S(t)$, with confidence limits and expert panel short/long delay cases for surgical facility

From the CTR file available for this analysis, times from POI to STP/FRSS entry averaged about 49 minutes for 90 records that had complete POI and surgical facility entry timing data. It is believed that the large majority of these records corresponded to the MD SME case, with no intervening treatment after the first responder (i.e. no routing through a BAS before surgery entry). It seems logical to expect that the upper MD SME curve for a 30-minute delay would shift down for the 49-minute empirical delay and be closer to the upper CTR confidence limit; we make no attempt to estimate that shift. The Weibull curves for the 49-minute delay look very comparable in basic shape and location compared with the MD SME bounds, particularly for the entry times less than 75 minutes.

Some caveats are presented next:

- While these analyses appear to confirm the Weibull model and the survivability estimates are in a reasonable location on the graph shown in Figure 6, we did have a considerable amount of missing data on exit timings that were estimated by NHRC SMEs with OIF experience in the medical treatment and evacuation processes. Some 38% of the casualties were missing a CTR exit time that was added manually from field reports on evacuation events. These missing data were researched and resolved before any model fitting began.
- As mentioned at the outset, the quest for a best-fitting model for the timing of combat mortality is ongoing for each segment in the casualty flow path of treatment and evacuation. Only one segment was examined here. As additional injury results become available in the NMC CTR EMED, the Weibull distribution will be a first candidate with other distributions being applied as warranted. For modeling and simulation purposes, it would seem desirable to have one model that could be applied to all segments if an adequate single representation could be demonstrated. It would not be necessary, however.
- The MD SME results shown here are averages of the responses by nine MDs. The early results out to about 75 minutes track very nicely. Starting after 75 minutes, the Weibull curves tend towards the higher delay curve (120 minutes).
- No attempt is made to perform a statistical test of goodness between the MD SME panel and the empirical results. The graphical comparison seems adequate given the nature of the two sources.
- No attempt is made to integrate the SME results with the empirical results to arrive at a combined best estimate of the Weibull parameters for surgical MTFs. Related evolving material in the literature, most notably by Singpurwalla^{23,24} and Keller-McNulty and Wilson,²⁵ seems applicable but is beyond the scope of

this research effort at the moment. It was our objective to demonstrate how comparable the two results are and then use the often easier to acquire SME opinions for areas where empirical data are not now available such as the early interventions in Figure 1.

6. Summary and Future Activities

Our main objective was to determine whether a statistical model could adequately describe empirical mortality events in a casualty's medical treatment flow. This effort is directly related to confirming the efficacy of the mortality modeling approach used in TML+. Considerable effort was devoted to obtaining complete CTR records concerning timing of injuries, either at the POI, or entries and exits at MTFs. Although not reported on here, we also spent considerable effort before ISS values were available in exploring the use of data-mining methods to identify LT injuries from the CTR records; the interested reader is invited to see the companion NHRC technical report.¹¹

Of the records with an ISS score of 25 or higher, 160 had both entry and exit timing information at a surgical MTF and were judged adequate for a statistical analysis. As only limited path data were available on when the injury occurred and where a patient had been, the effects of delay time in getting to a surgical facility was not addressed. Only the one path through a first responder to a surgical MTF was deemed adequate to consider.

The results obtained were very good: the probability of survival curve (with approximate 95% confidence limits) in surgical facilities for high-risk patients showed a strong graphical agreement with results inferred from the 2003 MD SME panel. Parameter estimates for the Weibull distribution were made using both graphical and analytical methods.

While the results apply to just one of the medical intervention types in TML+, they are very encouraging for two reasons:

1. they strongly reinforce the continued use of the Weibull distribution for use in TML+ in surgical MTFs; and
2. they help to confirm NHRC's reliance on special panels to provide expert opinions when empirical results are unavailable.

As the comparison of empirical and MD SME results is so impressive in the case presented, it seems justifiable to continue using the MD SME inferred Weibull modeling results for the other medical intervention facilities and mortality risk categories used in TML+ until other empirical data become available.

The CTR data set continues to grow, which could enable refinement of the conclusions in this paper by applying

similar analyses to other medical intervention facilities or operational theaters. A few possible research paths include the following:

- Considering Figure 1 again, it would be very interesting to have early mortality data, before a surgical MTF, to study for the steeper curves that more dramatically impact casualty mortality.
- Any delay effect from the POI on the Weibull results at the surgical MTFs was not examined as too few cases would have resulted due to missing entries for the time of injury. It seems important to obtain more empirical data to look at this important concomitant variable for the Weibull model in surgical facilities.
- These results were obtained from OIF CTR woundings. It would certainly be interesting to examine these findings with Operation Enduring Freedom (OEF) Afghanistan injury data if sufficient records were available.

These suggested research items would be logical next steps in pursuing a deeper understanding of battlefield mortality statistical modeling for tactical medical logistics studies and analysis and future decision aid developments. We also intend to pursue other more general objectives as described below to enhance our medical network modeling and simulation tools and input data sets to increase their validity for medical planning efforts such as force sizing and resource allocation.

Medical modeling and simulation provides a continually growing contribution to the development of Department of Defense medical policy, campaign testing and evaluation, technology Research, Development, Test, and Evaluation (RDT&E) and medical cost-benefit risk assessment. As the interest in medical modeling and simulation grows, so does the complexity of the tasks to which it is applied. Medical planners now routinely use TML+ and related tools to project medical resource, personnel, and transportation requirements. However, as these capabilities become accepted as the norm, their attention is increasingly focused on more complex issues associated with global cost assessment, crisis action planning, and human mortality and morbidity projection. These evolving areas of interest, however, require substantial investments in research dollars to validly define and quantify outcome measures in complex modeling and simulation tools. The NHRC with its technology partner, Teledyne Brown Engineering, is rapidly moving towards the development of the empirical data necessary to support accurate medical outcome projections in these areas. Recent advances in developing knowledge bases sufficient to support these evolving initiatives include the establishment and growth of the CTR EMED with its rich casualty medical and rehabilitative outcome data. These data have allowed NHRC to project global cost assessment, develop crisis action planning tools, and project human mortality and morbidity using empirical

data beginning with the generation of the casualty at the point of injury and continuing on to rehabilitative outcome.

Disclaimer

The opinions or assertions contained herein are the private views of the authors, and are not to be construed as official, or as reflecting views of the Department of the Navy or the Department of Defense.

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Mike Galarneau, MS, NREMT is a research investigator at the Naval Health Research Center (since 1991). He is the

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Paula Konoske, PhD, is the Head of the Medical Modeling and Simulation Department at the Naval Health Research Center in San Diego. The group conducts analyses and develops models to provide medical decision support to operational commanders, medical logisticians, and field medical personnel as they seek to determine the medical personnel and resources required to support combat, peacetime, and humanitarian assistance deployments.